AN ANALYSIS OF THE STATISTICAL REPORT OF ELVIRA SISOLAK

in the matter of

EEOC and Kathy Koch v. LA Weight Loss Centers, Inc.
Case No. WDQ-02-CV-648

by

Leonard A. Cupingood, Ph,D.
Director

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August 11, 2006

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I. INTRODUCTION

I am currently a Director in the Philadelphia office of LECG, LLC. I have been conducting statistical analyses of employment selection processes, most often within the context of employment discrimination litigation, for approximately 25 years. My vita is attached as Exhibit 1 to this report. I am being compensated at a rate of $525 per hour for preparation of this analysis and any work performed thereafter. A list of documents which I reviewed and relied on for this report is attached as Exhibit 2.

I have been asked by counsel for Defendant (LA Weight Loss or "LAWL") to review and comment on the statistical analysis prepared on behalf of EEOC by Elvira Sisolak. Ms. Sisolak's empirical objective, stated on page 1 of her report, was to present an analysis of LAWL's hiring activities:

> "… to determine if their hiring of men corresponded to the availability of
> men for such employment."

In her report, Ms. Sisolak presents tables and figures derived from a hodgepodge of different data bases which appear to be inconsistent with each other with regard to counts of hires and applicants.

<u>Notably, Ms. Sisolak never directly compares actual hires with applicants who are applying for the same jobs in the same state or even in the same market area at the same</u>

approximate point in time. To the contrary, Ms. Sisolak offers numbers that are misleading and present no valid statistical evidence that similarly situated men and women who apply for comparable openings have different rates of selection for those jobs. The bases for these statements follow in the remainder of this report. I first present a brief discussion of some requirements of a proper statistical analysis. I then review the various discussions and numbers presented in Ms. Sisolak's report.

II. THE STANDARDS OF COMPARATIVE STATISTICAL ANALYSIS

A statistical analysis offered as evidence in an employment discrimination claim against some employment process requires the analyst to do four general things. First, the analyst must establish the actual set of outcomes or decisions resulting from that process (e.g., the gender composition of those actually hired as Sales Counselor). Second, the analyst must estimate the set of outcomes one would "expect" to have occurred if the challenged decision process were free of the alleged discrimination. Third, the analyst must derive a "disparity" estimate (e.g., the "shortfall" of male Sales Counselor hires). Fourth, the analyst must conduct a statistical significance test to allow the fact-finder[1] to judge whether that estimated disparity is the result of

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[1] On page 1 of her report, Ms. Sisolak states:

> "… I will conduct statistical tests to show the likelihood of the occurrence of the differences between the expected and actual number of men. From the test results, I will determine whether these differences can be explained by chance. If chance cannot explain the difference, then the analyses have yielded a result called statistical significance that has been found by the courts and EEOC to be an indication of employment discrimination."

It is the fact finder's role, not Ms. Sisolak's role, to determine whether a particular disparity could be explained by simple random chance variation. The role of the analyst is to organize the available information in a legally meaningful way, to highlight key assumptions possibly bearing on the comparative analysis, to conduct analyses that reflect the decision process, to perform

simple random chance fluctuation (is it "statistically significant"?)[2].

The probative value of the analysis is entirely dependent on the second step … what set of employment outcomes would have obtained from a process free of discrimination? If the estimate of the "expected" process outcome is flawed, the consequent disparity estimate and test of statistical significance are meaningless. This, of course, begs the question of how one rationally determines what should have occurred from a process free of the alleged discrimination. It is with this view in mind that I comment on Ms. Sisolak's effort.

It is my understanding that the EEOC is pursuing both the disparate impact and disparate treatment theories of discrimination. As it is not at all clear from Ms. Sisolak's report, I must assume that an effort will be made to use her studies to support both of those theories.

It is my understanding that the disparate impact theory alleges that a challenged policy, practice or test, while ostensibly neutral on its face, disproportionately 'screens-out' members of a protected group. For example, a high school degree requirement as a condition of employment may disproportionately exclude African American as opposed to white job applicants. Importantly, discriminatory intent is not an issue in an impact claim. If impact is established, the employer would then need to demonstrate the business justification for that practice or test (e.g., the test reasonably predicts future job performance). In contrast, the disparate treatment theory of discrimination explicitly alleges discriminatory intent on the part of the employer.

These legal distinctions bear on the type of statistical evidence offered.

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appropriate tests of statistical significance and to report those results to the fact-finder at a level of aggregation consistent with the facts of the matter.

[2] A statistically significant disparity is traditionally defined as one with less than a one-in-20 likelihood of occurring due to random chance factors alone. This corresponds to a 2-tail probability of less then 0.05 or, equivalently, at least 1.96 units of standard deviation.

Since intent is the critical issue in a treatment claim, the probative value of the statistical analysis depends on the extent to which the analyst has limited the comparisons to "similarly-situated" persons or applicants. In other words, the analyst should account for the major measurable factors thought to legitimately impact the employment process outcome at hand (e.g., prior relevant experience, certifications). This is typically accomplished by using some form of regression or multiple pools analysis to accommodate those various factors. If the analysis does not account for such factors, the statistical inference offered from that analysis should not be relied upon as evidence supporting the treatment theory. Dr. Sisolok has conducted no such analysis.

In the context of an impact claim, the statistical analysis need not consider these factors to the same extent. The most basic example would be a challenge to a formal test (e.g., the written exam for a Fire Captain position) or job requirement (e.g., a height requirement for state troopers). In such cases, the analyst must identify the population of test-takers and, for each test-taker, ascertain protected status and whether they passed or failed the test. Then, the question is whether the pass rate for protected test-takers is substantially less than that for other test-takers (either from a statistical or practical perspective, as the fact-finder sees fit). There may be different versions of the "test" and, in such cases, the psychometric equivalence of those versions must be determined; also the applicant pool may be different for the various tests. These issues would need to be assessed to determine whether the data should be pooled or combined over multiple tests. If the test data cannot be pooled, a separate statistical analysis of the impact question should be prepared for each test.

When an impact claim is made against an employment process (as opposed to a traditional test), measurement and interpretation are much more difficult. However, I understand

that it is a plaintiffs' burden to isolate the impact of each identifiable "test" at issue, if possible, as opposed to performing a simplified and less enlightening "bottom-line" analysis

III. CRITIQUE OF PLAINTIFFS' EXPERT REPORT

A. Job Requirements

Pages 2-7 of the Sisolak report offer a number of descriptive tables regarding the "availability" of men in sales or customer contact occupations in various industry segments based on 2000 Census data. As there is ample data regarding actual applicants seeking employment with LAWL, these Census-based "availability" estimates are irrelevant to the question she sought to address.

To the extent that Ms. Sisolak is suggesting that these Census availability figures should be comparable to the jobs at issue in this matter, she has presented figures that are misleading, and likely biased in the favor of the EEOC. The most prevalent job at LAWL, Sales Counselor, has an annual salary below $25,000. The Census figures include employees at all income levels. Workers who earn more than $25,000 (overall and for Healthcare Support Occupations) would not generally be interested in these Sales Counselor jobs. Hence, Ms. Sisolak is overstating the male availability.

B. Data Bases

In pages 7 – 13 of her report, Ms. Sisolak discusses figures from a myriad of "data bases" that appear to be inconsistent, raising questions as to the reliability of her underlying data base analyses. Below is a summary of the "data bases" relied on by Ms. Sisolak:

Description	Source	Time Period	Number of Records	Page Number of Rept. Reference
Hires	Payroll File	Jan 2002 - Feb 2005	6,637	7
Hires	Personnel File	1999-2004	5,445	8
Employees	Employee Files	Unknown	15,787	10
Unsuccessful Applicants	Applications	2000 - early 2005	73,300	11
Applicants Not Hired	Access Data Base	2004 - 2005	27,369	12
Hires/Rejected Applicants	Access Data Base	Last Quarter 2004 – "Most" of 2005	54,929	13

The first two files above relate to hires. Ms. Sisolak reports more hires for a 3 year time period from January 2002 – February 2005 (6,637) than for a 5 year time period from 1999 – 2004 (5,445) which is largely a subset of the time period from the first file. This is illogical.

Ms. Sisolak then discusses 15,787 employee files in the context of a review of "Qualifications of Hires". Who are these 15,787 "hires"? When were they hired? If there were 5,445 hires from 1999 – 2004 (or 6,637 from January 2002 – February 2005), then are these 15,787 individuals employees who were hired well before 1999? If so, how can a study of their relative qualifications be of probative value for analyzing the decisions made during the relevant time period?

The last two data files in the above table purportedly relate to applicants for approximately the same time period of 2004 – 2005. However, in one instance, Ms. Sisolak says that there are 27,369 applicants, and in the second instance, she says there are twice as many

(54,929). Even allowing for the fact that the second group also contains hires cannot possibly explain the large discrepancy in counts of applicants for supposedly the same time period.

The fourth entry in the above table refers to 73,300 unsuccessful applicants from 2000 – early 2005. How can there be 54,929 hires/rejected applicants for approximately 1 year, but only 73,300 for more than 5 years?

C. Sisolak Table 10

Table 10 of the Sisolak report describes 29,742 "unsuccessful" applicants by gender during a 6-year time period for one of five positions. Presumably, "unsuccessful" means an applicant who was not hired according to the payroll file (see Table 11)[3].

Ms. Sisolak describes her applicant classification scheme as follows:

> "In classifying the job-applied-for, I classified persons as applying for Medical Assistant somewhat differently than other positions. Because this job has a specific requirement of certification as a phlebotomist, I categorized as Medical Assistant all persons who listed that job or any of its variations as any of the jobs they were applying for. For other positions, I categorized persons by the first job they applied for." (Sisolak, page 11, emphasis added).

This makes no sense. It is appropriate to classify all applicants by their originally stated job preference, even those applicants listing Medical Assistant as a secondary or tertiary job preference. If this latter group is disproportionately female (as is suggested by Ms. Sisolak's Tables 10 and 11), Ms. Sisolak's logic over-states the representation of males in the other job-applied-for categories.

Moreover, the certification requirement for Medical Assistant applicants should have caused Ms. Sisolak to exclude from her Medical Assistant analyses any applicant who did not

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[3] This definition of "unsuccessful" is problematic, since the source of the hiring information (the payroll file) covered slightly more than three years worth of hiring activity (see Sisolak Table 6) whereas the applicant data encompassed a 6-year period.

possess the requisite certification (or otherwise account for this characteristic). For reasons unknown, she chose not to do so.

D. Sisolak Table 11

The "unsuccessful" applicants from Table 10 (for the 2000 to 2005 period) and the "payroll" hires from Table 6 (for the January 2002 to February 2005 period) are placed side-by-side in Sisolak Table 11. For each job-applied-for category individually and then for all five categories collapsed into one[4], Ms. Sisolak statistically compared the gender composition of the hires to that of the unsuccessful applicants. She reports highly statistically significant disparities adverse to male applicants in each case (see Ms. Sisolak's Appendix C)[5].

The probative value of this presentation is questionable for a number of reasons.

First, Ms. Sisolak's Table 11 compares those hired to raw applicant flow data, referred to as a simple "bottom-line" analysis. Such analyses have a long history of being viewed with skepticism by judicial fact-finders:

> "An expert who supplies nothing but a bottomline supplies nothing of value to the judicial process." [FPC v. Hope Natural Gas, 320 US 591, 627, 64 S.Ct. 281, 88 L.Ed. 333 (1944)].

Second, Ms. Sisolak's analysis is akin to a comparison by gender of test pass rates among those taking one of five different paper-and-pencil tests (where a hire constitutes a "pass" and each applicant is assumed to be a "test-taker"). In this case, however, there are discrete steps in

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[4] When Ms. Sisolak pools all applicants into one category, she is making an assumption that she should know to be false … that all applicants have the same likelihood of being hired, regardless of the position actually sought. For example, her presentation assumes that a Sales Counselor applicant and a Medical Assistant applicant both have the same likelihood of being hired as a Medical Assistant.

[5] It should additionally be mentioned that the Fisher's Exact Test used by Ms. Sisolak here and throughout her report is invalid for the situations to which she has applied it. The Fisher's Exact Test is applicable to a fixed population of applicants who can be classified into two groups, e.g., hired and non-hired. Ms. Sisolak is applying the Fisher's Exact Test to situations with independent groups of applicants and hires who are not even from the same time period.

the actual hiring process (each equivalent to a distinct "test"). For example, applicants not surviving the prescreen stage or who fail to appear for a scheduled interview or who accept alternative employment cannot possibly pass Ms. Sisolak's "test" (be hired). If the interest is in hiring outcomes, it is clearly the case that the appropriate pre-selection population should consist only of those applicants who were actually interviewed, i.e., those who in fact took that "test."[6]

Third, Ms. Sisolak's "unsuccessful" applicant populations no doubt include many applicants to whom an employment offer was extended but not accepted. Thus, whereas Ms. Sisolak intended her focus upon "hires" to be an accurate reflection of decision-making by LAWL hiring managers, the fact that a "hire" also requires a decision on the part of the applicant makes it unclear what her disparity measures mean in terms of defendant's decision-making.

Fourth, to the extent that Ms. Sisolak's analyses will be offered in support of a disparate treatment claim of discrimination, her work falls woefully short of the mark. As the cornerstone of a disparate treatment claim is the discriminatory intent of the employer, it is the analyst's obligation to the fact-finder to ensure that the statistical comparisons be made among "similarly-situated" applicants. That is, the analysis must statistically account for the major measurable and legitimate non-discriminatory factors thought to impact the decision process in question. At best, Ms. Sisolak's analysis accounts for only one such factor, the principal job sought by the applicant[7]. Ms. Sisolak's analysis is devoid of any recognition that applicants seeking employment at different LAWL centers[8] or at different points during the analysis period are not competing against one another. Ms. Sisolak pretends that, indeed, all applicants are reviewed at

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[6] Sisolak Table 13 makes an attempt to do so but this analysis suffers a new set of flaws.

[7] However, her "Total" comparisons (across the five job categories) are meaningless as they fail to account for even this basic characteristic.

[8] Ms. Sisolak reports that her 6,637 hired applicants were initially assigned to one of 350 LAWL centers in 21 different states (Sisolak page 8).

the same instant in time and that an applicant interested in employment in Southern California is competing for the same position with applicants in Philadelphia, Palm Beach or numerous other work locations. She should have structured her studies to deal with the 90-day shelf-life of an employment application and the location preferences indicated by applicants.

Fifth, a proper disparate treatment analysis would further account for the presence or extent of any relevant "qualification" factors (e.g., the certification requirement for Medical Assistant applicants). Again, no such consideration was incorporated into the Table 11 hiring studies.

E. Sisolak Table 12 ("Applicants Not Hired")

Table 12 of the Sisolak report offers the distribution of "rejection" reasons for 28,457 non-hired applicants in 2004-2005. The utility or importance of this table is not evident, since Ms. Sisolak appears to offer no opinion based on that table other than to observe that: (1) about 70 percent of all "rejected" applicants are rejected on the grounds of "relevant experience"[9]; and (2) about 15 percent of these applicants remove themselves from the process (self-selection) for reasons related to lack of interest, pay expectations, work schedule or commute-to-work issues. Table 12 does not include those applicants who also were not hired simply because they could not be contacted, because they failed to return phone messages or were "no shows" for scheduled interviews. It is my opinion that such an applicant is just as much a case of "self-selection" as the applicant who was reached by phone but indicated "no interest" or a "commuting" problem, since their failure to respond or follow-up is effectively an expression of no interest in the position.

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[9] It is curious to note that Ms. Sisolak chose not to show these outcomes by gender.

Regarding these "self-selected" applicants, it can hardly be said that the failure to hire them had anything to do with LAWL decision-making. Such cases are irrelevant to any credible study of hiring decisions, yet such applicants doubtless appear in large numbers in Sisolak Table 11. This is in contrast to Ms. Sisolak's claim on page 10 that about half of the employees did not have any experience in the industries or occupations mentioned by LAWL's hiring officials. This suggests that Ms. Sisolak's definition of the 6 categories of prior experience on page 10 is deficient and may not contain all "relevant experiences" of an applicant.

F. Sisolak Table 13 ("Steps in the Hiring Process")

This table is based upon electronic applicant flow data from 2004-2005 and, for a subset of 23,101 gender-identified applicants, attempts to track the relative success of male and female applicants as they reach various stages of the hiring process. There appear to be three "decision points" at issue in this table:

(1) the likelihood of being rejected before any telephone prescreening;
(2) the likelihood of being rejected, among those subjected to the telephone prescreen;
(3) the likelihood of being hired, among those actually interviewed.

As 18.9 percent of all applicants in this table are male, the suggestion is that, absent discrimination, one would expect to see 18.9 percent male among the set of applicants 'surviving' to each stage of the process.[10] As presented, the table suggests that the major stumbling block to male success is the decision process relating to "Rejected Prior to Pre-Screening."

The hiring rate disparity from Table 13 (conditioned only on interviewed applicants) yields a much lower level of "statistical significance" than the hiring rate disparity from Table 11

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[10] This requires the heroic assumption that there are no differences by gender in the distribution of salient qualifications, the timing of applications for specific openings, or the specific markets/centers to which applicants seek employment.

(premised upon simple overall raw applicant flow data). Again, this "result" assumes that all applicants were applying for all positions over the whole time period. We know that this cannot possibly be true. For example, how can someone who submits an application in 2005 be an applicant for a position in 2004? This difference has two explanations: (1) Table 13 deals with a smaller number of hires than Table 11; and (2) the proportion male among the hires is much more in line with the proportion male among those interviewed than with the proportion male among all applicants.

Whereas Table 13 suffers the same flaws as Table 11 (i.e., failure to account for applicant timing, geographic preferences and relevant qualifications), it suffers two additional flaws. It co-mingles applicants seeking different positions. This is obviously a step backwards from Table 11.

The second flaw relates to how Ms. Sisolak has classified applicants in her Table 13. She indicates that she placed each applicant "at the highest single point reached in the selection process" (Sisolak page 13). However, inspection of her computer logic indicates otherwise. It is true that if there was any evidence in the data set that the applicant was hired, that applicant was indeed treated as "hired" in Table 13. Presumably, the next highest state would relate to applicants who were offered employment but declined that offer. Such cases obviously were not rejected prior to the pre-screen, did pass the pre-screen and were interviewed. In fact, if they were offered employment, they should be counted as a "hire", not a rejected applicant. Ms. Sisolak also mis-classified numerous applicants who had interviews scheduled or were pre-screened as "rejected prior to pre-screening".

Given the apparent importance of the "Rejected Prior to Pre-Screening" classification as a male 'stumbling block', I focused on the 12,111 applicants so classified in Table 13 by Ms.

Sisolak. For these cases, I reviewed the electronic applicant data and found the following numbers with the indicated comment in one of the five "results" fields:

Applicants Classified as Rejected Prior to Pre-Screen	
Number	Tracking Comment
615	Interview Scheduled
110	Second Interview Scheduled
417	Left Message
18	No Call Back
20	E-Mailed
69	Prescreened-Rejected
43	Prescreened-Good
3	Prescreened-No Call Back
2	Keep on File
6	No Show
4	Sent to Field
1,307	Total

If these applicants were indeed rejected based upon the initial review of the application/resume, we would not encounter these types of applicant tracking comments. Moreover, 817 of Ms. Sisolak's 12,111 "rejections" appear in the interview schedule file with a scheduled interview date. There are clearly some important issues with Ms. Sisolak's interpretation of the electronic data.

G. Hiring Selections Among Those "Interviewed"

Accepting *arguendo* Ms. Sisolak's somewhat questionable classification scheme for Table 13, I sought to determine what her hiring analysis would look like if we statistically limited the gender comparisons to applicants seeking the same position in the same market during the same year and quarter. For simplicity, I focused on applicants seeking one of the five

positions studied in Ms. Sisolak Table 11[11]. For each job-applied-for, the estimated shortfall of male hires and associated standard deviation measure is:

Sisolak Table 13 Hire Analysis by Job Sought			
Job Sought	Hires	Male Hire Shortfall (Surplus)	Standard Deviations[12]
Asst.Mgr.	40	1.9	1.55
Area Supv.	1	0.0	0.00
Center Mgr.	30	1.5	0.99
Med.Asst.	41	(1.4)	1.06
Sales Couns.	271	3.6	1.38

On this more realistic comparison basis, there are no statistically significant gender disparities in any job classification. To the extent relevant, one can statistically combine these results, yielding a net shortfall of 5.5 male hires, equivalent to 1.82 units of standard deviation. By contrast, the Sisolak "Hired/Not Hired" study (ignoring job sought, timing and geography) yields a 1-tail chance probability of 0.0111 (Appendix C), equivalent to 2.29 units of standard deviation. This shows that the statistical outcomes are affected by consideration of the job-applied-for, market area, and time-of-application factors. In my opinion, Ms. Sisolak has offered no credible statistical evidence that hiring selections from the group of applicants she believes were interviewed was anything but gender-neutral.

Leonard A. Cupingood
Leonard A. Cupingood, Ph.D.

August 11, 2006
Dated

[11] There are 22,585 applicants and 382 hires across these five job-applied-for categories, meaning that Table 13 includes about 500 applicant records relating to other positions.

[12] Whereas Ms. Sisolak's Appendix C statistical findings are expressed in chance probability terms, these statistical significance findings are expressed in standard deviation units (a disparity of at least 1.96 standard deviations corresponds to a chance probability of less than 0.05).

EXHIBIT 1

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SUMMARY
Leonard Cupingood received his B.A. degree in Mathematics from Rutgers University and his M.A. and Ph.D. degrees in Statistics from Temple University.

He has extensive experience in conducting statistical analyses for employment discrimination cases in the areas of hiring, initial placement, wage disparities, transfers, promotions, layoffs, terminations, disciplinary actions and calculation of net liability both on an individual and class basis. In support of these efforts, he has provided deposition and trial testimony both as a data base expert and as a statistician. Dr. Cupingood also has expertise in preparing work force utilization analyses with respect to minority and female representation, and in the comparison of the racial composition of jury wheels to the racial composition of the underlying geographic areas.

Dr. Cupingood has expertise in the design and selection of scientific random samples which are used to support statistical analyses and expert testimony. In particular, he has been responsible for the design of random samples used for the selection of employees in random drug test programs.

Prior to joining LECG, Dr. Cupingood was Vice President of the Center For Forensic Economic Studies. Prior to his tenure at the Center for Forensic Economic Studies, Dr. Cupingood participated in numerous evaluations of social programs for the Department of Labor and Housing and Urban Development. His responsibilities included construction and validation of large-scale databases, statistical impact analyses, and preparation of reports documenting the findings of the studies.

Dr. Cupingood is a member of the American Statistical Association. His article on the seasonal adjustment of time series appeared in *The Journal of Business and Economic Statistics*.

LECG

EDUCATION
Ph.D., Statistics, Temple University, 1985
M.A., Statistics, Temple University, 1979
M.A., Mathematics, Temple University, 1972
B.A., Mathematics, Rutgers1968

PRESENT POSITION
LECG, Director, 2003 to present

TEACHING EXPERIENCE
Villanova University, Adjunct Assistant Professor in Statistics, 1987 to 2000.
Temple University, Instructor in Statistics, 1983 to 1985.
Drexel University, Instructor in Mathematics, 1978 to 1981.

OTHER POSITIONS HELD
The Center For Forensic Economic Studies, Vice President, 1981 to 2003.
National Economic Research Associates, Inc., Senior Consultant, 1986 to 1991.
Center For Forensic Economic Studies, Ltd., Consultant, 1981 to 1986.
Ketron, Inc., Senior Analyst, 1972 to 1981.
Leeds and Northrup Company, Programmer, 1968 to 1972.

ACTIVITIES AND HONORS
Court Appointed Consultant

1. Appointed as automation consultant to the Special Master in the U.S. District Court for the Eastern District of Pennsylvania; advised the court regarding the adequacy of a computer system for monitoring the referral and dispatching process of a Union operating under the Court's supervision.

Actuarial Examinations

1. Passed Actuarial Examinations in mathematics, probability and statistics, compound interest and mathematics of life contingencies.

Professional Activity

1. Member, American Statistical Association.

LECG

PUBLICATIONS/REPORTS (Last 10 Years)

L. Cupingood, "Use of Statistical Models to Provide Statistical Evidence of Discrimination in the Treatment of Mortgage Loan Applicants: A Study of One Lending Institution," *Mortgage Lending, Racial Discrimination and Federal Policy*, Urban Institute Press, 1996, J. Georing and R. Wienk, eds.

L. Cupingood, "ARIMA Estimates of Stock Option Prices" presented at the annual meeting of the American Statistical Association, Anaheim, California, August 1990.

L. Cupingood, D. Griffin and B. Siskin, "Economic Damages in a Wrongful Discharge Matter," presented at the American Bar Association's Mid-Winter Meeting in Palm Springs, California, 1990.

L. Cupingood, "The Measurement of Time Delay Between Input and Output Processes," presented at the annual meeting of the American Statistical Association, San Francisco, CA, August 1987.

L. Cupingood and W. Wei, "Seasonal Adjustment of Time Series Using One-Sided Filters," *Journal of Business and Economic Statistics*, October, 1986.

L. Cupingood, "Linear Filtering and the ARIMA Approach to Seasonal Adjustment and Stock Option Pricing," Temple University, unpublished Ph.D. dissertation, 1985.

SPEECHES

"By the Numbers: CRA/HMDA & Fair Lending Compliance Colloquium," PCI Services, Inc. Seminar, June 1997.

"Statistical Issues in Litigating Employment Discrimination Claims," Federal Publications Seminar, 1993 - 1995.

"Application of Scientific Evidence in the Courtroom," Temple University Law School, 1993 - 1995.

"Economic Damages in a Wrongful Discharge Matter," The American Bar Association's Mid-Winter Meeting in Palm Spring, California, 1990.

Testimony Listing for Leonard A. Cupingood, Ph.D.

Date	Case Name	Location	Activity	On Behalf Of
2006	Exelon Corp	Philadelphia, PA	Declaration	Defendant
2006	J. McDowell v. Phila Housing Authority	Philadelphia, PA	Trial	Plaintiff
2006	K. Moyer v. PPG	Pittsburgh, PA	Testimony	Plaintiff
2005	Brooks et al v. First Union	Somerset, NJ	Deposition	Defendant
2005	E. L. Anderson et al. v. The Boeing Company	Philadelphia, PA	Declaration	Plaintiff
2005	Soloman Williams, et al. v. Boeing, et al.	Seattle, WA	Trial	Plaintiff
2003	Sonii v. General Electric Co.	Chicago, IL	Affidavit	Plaintiff
2002	U.S. v. Belleville, IL	St. Louis, MO	Affidavit	Plaintiff

EXHIBIT 2

Documents Reviewed

1) Report on the Hiring of Men by LA Weight Loss Centers, Inc. Elvira Sisolak, May 25, 2006.

2) Databases supplied as part of the EEOC/Sisolak data production.

3) ACCESS databases provided by LA Weight Loss, Inc.

4) E-mail from Cathryn Marsh to Aliza Karetnick, August 11, 2006.